Attitudes towards mode choice in Switzerland

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Abstract

We integrate latent attitudes of the individuals into a transport mode choice model through latent variable and latent class models. Psychometric indicators are used to measure these attitudes. The aim of the inclusion of attitudes is to better understand the underlying choice preferences of travelers and therefore increase the forecasting power of the choice model. We first present an integrated choice and latent variable model, where we include attitudes towards public transport and environmental issues, explaining the utility of public transport. Secondly, we present an integrated choice and latent class model, where we identify two segments of individuals having different sensitivities to the attributes of the alternatives, resulting from their individual characteristics. The calibration of these types of advanced models on our sample has demonstrated the importance of attitudinal variables in the characterization of heterogeneity of mode preferences within the population.

Keywords: Discrete choice, structural equation models, attitudes, latent classes, latent variables, transport mode choice, attitudinal indicators, revealed preferences

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1 Introduction

Transport mode choice behavior of the individuals is explained by socio-economic characteristics and attributes of the mode. However these are not the only variables that explain heterogeneity in the mode preferences. It has been well accepted that attitudes and perceptions play an important role in the decision-making process (McFadden, 1986). Attitudes and perceptions cannot be directly observed from the data and hence considered *latent variables*.

Structural equation models (SEM) provide a powerful methodology to translate attitudes and other latent variables into a statistical model (Bollen, 1989). SEM has been widely applied in social sciences (Bielby and Hauser, 1977). An early example of such application is the evaluation of the effect of an individual's occupational aspiration, as a latent variable, on his best friend's (Duncan et al., 1968). Later, the development of Linear Structural Relation (LISREL) model (Joreskog et al., 1979) contributed to a wider use of SEM in social sciences. One of the major difficulties in SEM is the collection of adequate measurements for the latent variable, since it cannot be observed directly from the data. Research in this context has been concentrating on the measurement of attitudes via psychometrics (Likert, 1932, Bearden and Netemeyer, 1999, Schüessler and Axhausen, 2011) and more recently by generating data from words (Kaufmann et al., 2010).

In transport research, attitudinal variables are studied to explain the travel behavior of individuals through structural equation models. Golob (2003) provides a detailed literature review on numerous applications of SEM in transport. Scheiner and Holz-Rau (2007) analyze the interrelation between socioeconomic characteristics, lifestyle, residential choice and travel behavior of the individuals. Structural equations are developed by using data from a survey in Cologne, Germany. They have found out that lifestyle preferences play a key role in the residential choice of individuals, which in turn has an important impact on the travel mode choice. Similarly, Van Acker et al. (2010) study how residential and travel attitudes affect the decision of residential location and travel behavior with data from an Internet survey in the region of Flanders, Belgium. It is shown that car ownership is significantly affected by the residential attitudes. Furthermore, Van Acker et al. (2011) extend the model by including interrelations between residential and travel mode choices for leisure trips. They point out that the strength of interrelations depends on the mode as well as the activity performed. They also come up with different lifestyle characteristics that result in different decisions on travel mode. By comparing the models with and without lifestyle characteristics, they conclude that there is an improvement in terms of the explained variance in mode choice, with the inclusion of these subjective variables.

The structural equation models of attitudinal variables are integrated into choice models, in order to make use of simultaneous estimation of choice and attitudinal variables. These integrated models are called hybrid choice models, which are introduced by Ben-Akiva et al. (1999), Walker and Ben-Akiva (2002) and Ben-Akiva et al. (2002). They provide a general framework where attitudinal variables are considered as latent variables. These variables are introduced in the choice context through latent variable models and latent classes.

In integrated choice and latent variable models, the attitudinal variables are included as explanatory variables of the choice. Vredin Johansson et al. (2006) analyze the effect of the latent variables of environmental preferences, safety, comfort, convenience and flexibility on the mode choice using a sample of Swedish commuters. They provide insights for policy-makers so as to improve the transport systems through the use of the attitudinal variables. Espino et al. (2006) study the mode choice behavior for suburban trips by including the latent variable of comfort. Abou-Zeid et al. (2010) explain the variability in individuals' willingness to pay, with individuals' attitudes toward travel, through a latent variable model. They introduce a *car-loving* attitude and show that the individuals who dislike public transport are more sensitive to the time and cost changes of public transport compared to others.

Latent class models are used to identify different classes of individuals by making use of the attitudinal variables (Collins and Lanza, 2010). Different classes may have different taste parameters, choice sets, and decision protocols. Ben-Akiva and Boccara (1995) study the mode choice behavior of commuters and allow different choice sets for different segments of the population. Gopinath (1995) presents latent class models for mode choice behavior and shows that different segments of population have different decision protocols for the choice process as well as different sensitivities for time and cost. Hosoda (1999) works on the mode choice models for shopping trips where both latent variables and latent classes are included in the framework. It is shown that without a proper modeling of heterogeneity in the sample, there can be significant bias in the parameter estimates, even for travel time and travel cost. Therefore attitudinal variables are proposed to be included through appropriate hybrid choice models. More recently, Walker and Li (2007) study lifestyle preferences with a data from Portland, Oregon. They identify different latent classes of individuals that have different residential location choices, resulting from their lifestyle preferences.

In this paper we present models that integrate attitudes into choice context through latent variables and latent classes. These latent variables and classes are identified with psychometric indicators that are related to the attitudes of individuals in the context of transport modes. With the presented models, we show that the attitudinal variables have significant impacts on the transport mode preferences. The models show two different methodologies to integrate attitudinal variables in a mode choice context. In the first model heterogeneity in the sample is captured through latent attitudinal variables and in the second model through a latent segmentation of the population. We show that the models are operational in the sense that they can be used in order to predict the market shares for different transport modes; to compute elasticities of demand and willingness to pay for individuals. Moreover, in the area of behavior modeling, the presented models are advanced behavioral models compared to classical models and the resulting complexity brings in a better understanding of the travel behavior.

For the preliminary analysis regarding the same research we refer to Atasoy et al. (2010) and Atasoy et al. (2011) where latent variables or classes are used to better explain the travel behavior.

The rest of the paper is organized as follows: section 2 summarizes the data collection campaign. Section 3 provides the model specification and estimation results regarding the integrated choice and latent variable model and the integrated choice and latent class model. In section 4 we present the validation of the model and the analysis of demand indicators including market shares, demand elasticities and values of time (VOT). Finally we conclude and discuss the future directions of our research in section 5.

2 Data Collection

A comprehensive data collection campaign is carried out between 2009 and 2010 within the framework of a collaborative project between PostBus and the Ecole Polytechnique Fédérale de Lausanne (EPFL) on travel mode choice. PostBus is the public transport branch of the Swiss postal service, which typically serves in low-density areas of Switzerland.

The first step of the data collection campaign was a qualitative survey conducted by the Urban Sociology Laboratory (LASUR) of the Ecole Polytechnique Fédérale de Lausanne (EPFL). It consisted of interviews of 20 individuals in the Swiss canton of Vaud, the purpose of which was to obtain information on their mobility habits and residential choice. In addition to the interviews, all trips of the respondents were recorded using GPS devices. A complete description of the qualitative survey is reported in Doyen (2010). The qualitative survey provided important insights about the individuals' opinions on transport modes. These outcomes were used in the construction of a revealed preferences (RP) survey.

The second step consists of the RP survey, which is the data source used for the models presented in this paper. Data on the mobility of inhabitants of suburban areas of Switzerland was collected. Questionnaires were sent to households in 57 towns/villages, which were selected in order to be representative of the PostBus network. For small villages, all the households were included in the sample. For larger towns the sample included all the households in the center and a portion of the surrounding neighborhoods. In total 28'193 respondents received a questionnaire and in return 1763 valid questionnaires (6.25%) were collected. Respondents were asked to report information about all trips performed during one day, including origins, destinations, travel durations, costs, chosen modes and activities at destination. In addition, data about the respondents' opinions on topics related to environment, mobility, residential choice or lifestyle were collected, as well as information about their mobility habits, perceptions of various transport modes, household composition and socio-economic situation. Part of the survey that was dedicated to collect information on opinions, included a series of 54 statements. The respondents had to rate their level of agreement on a five-point Likert scale (Likert, 1932) ranging from a total disagreement (response of 1) to a total agreement (response of 5). These statements, refered as *psychometric indicators*, were designed on the basis of examples in the existing literature (see Kitamura et al., 1997, Redmond, 2000, Ory and Mokhtarian, 2005, and Vredin Johansson et al., 2006) and using the outcomes of the qualitative survey mentioned above.

Examples of the sentences related to the environmental concern of respondents in the revealed preference survey are reported below:

- I am concerned about global warming.
- We should increase the price of gasoline to reduce congestion and air pollution.
- We must act and take decisions to limit emissions of greenhouse gases.
- We need more public transport services, even if taxes are set up to pay for the additional costs.

In this paper, we present discrete choice models which aim at identifying the factors driving individuals' mode choices over the reported sequences of trips departing from their home and returning to that same place. For instance, a sequence of trips could include a first trip from home to work, a second trip from work to leisure, and a last trip from leisure to home. For each of these sets of trips, the main mode was identified. Therefore, the data we used for estimating the models presented in this paper consists of 2265 sequences of trips reported by 1763 respondents.

It is to be noted that due to the inaccuracy of the travel durations and costs reported by the respondents for each of their trips, the times and costs used in the models presented in this paper were imputed using the websites of the Swiss railways (SBB) `http://www.cff.ch` and of ViaMichelin `http://fr.viamichelin.ch`. To be able to use these websites, for each trip, we entered the origin and destination information which was reported by the respondents. The same websites were used to infer the times and costs for the non-chosen alternatives.

In this sample, some socio-demographic categories were oversampled, i.e. individuals with a high education level, male respondents or individuals aged between 40 and 79 years. The proportions of individuals in each category in the sample and in the population of the regions considered in the survey are reported in Table 2. For the percentages of each socio-demographic category in the population, we report the data of the Federal Census of 2000.

Table 1: Proportions of socio-demographic categories

Category		Sample	Population
Education			
	University	14.2%	6.2%
	Vocational university	16.2%	10.6%
	Certificate of Vocational Training and Education	61.0%	50.9%
	Compulsory school	7.6%	27.6%
	No school diploma	1.0%	4.7%
Age			
	16-19 years	2.3%	8.2%
	20-39 years	21.2%	33.4%
	40-64 years	55.9%	41.6%
	65-79 years	18.7%	12.7%
	80 years and above	1.8%	4.1%
Gender			
	Male	53.0%	49.0%
	Female	47.0%	51.0%

In section 4.1, we are presenting the aggregate indicators of demand including, market shares, elasticities and value of time. These indicators must be computed by weighting each observation of the survey according to the representation of its age category, gender and education level in the regions considered in the survey, in order to evaluate the real demand for private motorized modes, public and soft transport modes in these regions. The weights are calculated by applying the *iterative proportional fitting (IPF)* algorithm.

3 Model Specification and Estimation Results

The two models are represented by Figures 1 and 2. Observed variables such as explanatory variables, psychometric indicators, and choices are represented by rectangular boxes and latent variables such as utilities, attitudinal variables, and classes are represented by ovals. Structural equations are represented by straight arrows while measurement equations are represented by dashed arrows.

The model pictured in Figure 1 is called the *continuous model*, since latent attitudes are integrated as continuous explanatory variables in the choice model. It consists of two components: a latent variable model and a discrete choice model.

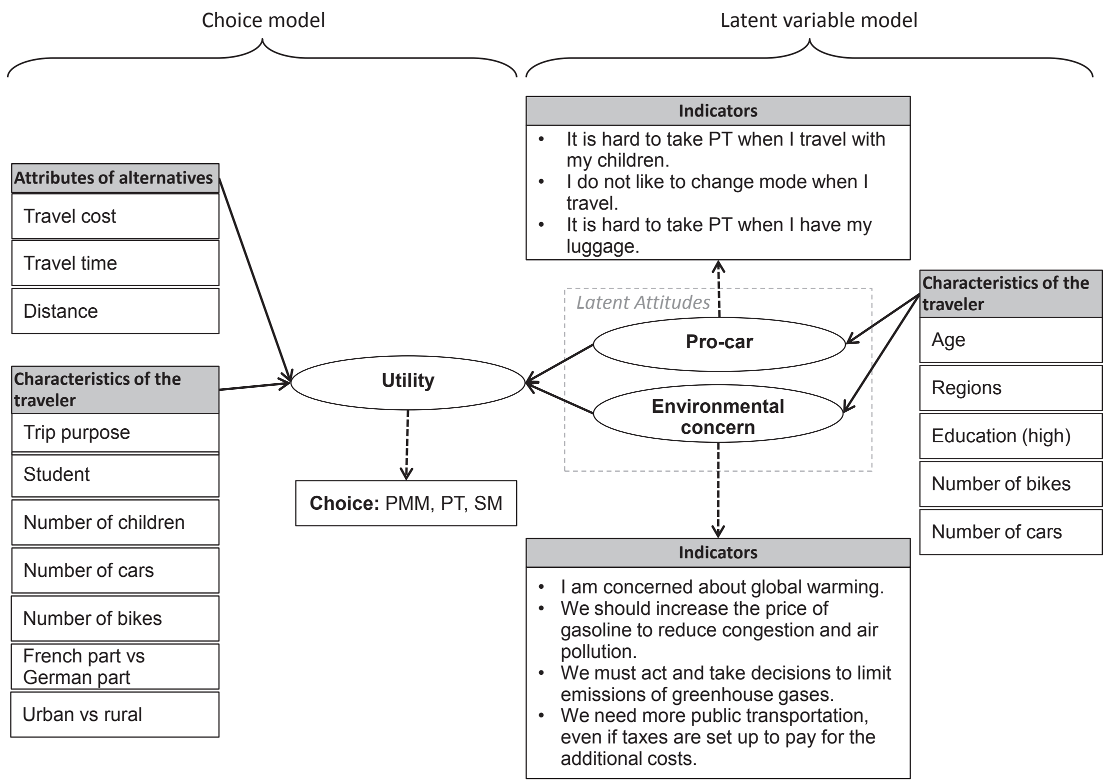


Figure 1: Continuous model framework

The model in Figure 2 is called the *discrete model*, since two separate choice models are specified for the two latent classes. These classes are identified by attitudinal indicators. The integrated model is composed of a latent class model and two class-specific choice models.

As a base reference we estimate a logit model, which has the same specification as the choice models included in the continuous and discrete models. In sections 3.3 and 4 we use this base model as a reference to evaluate the added value of latent variables and classes.

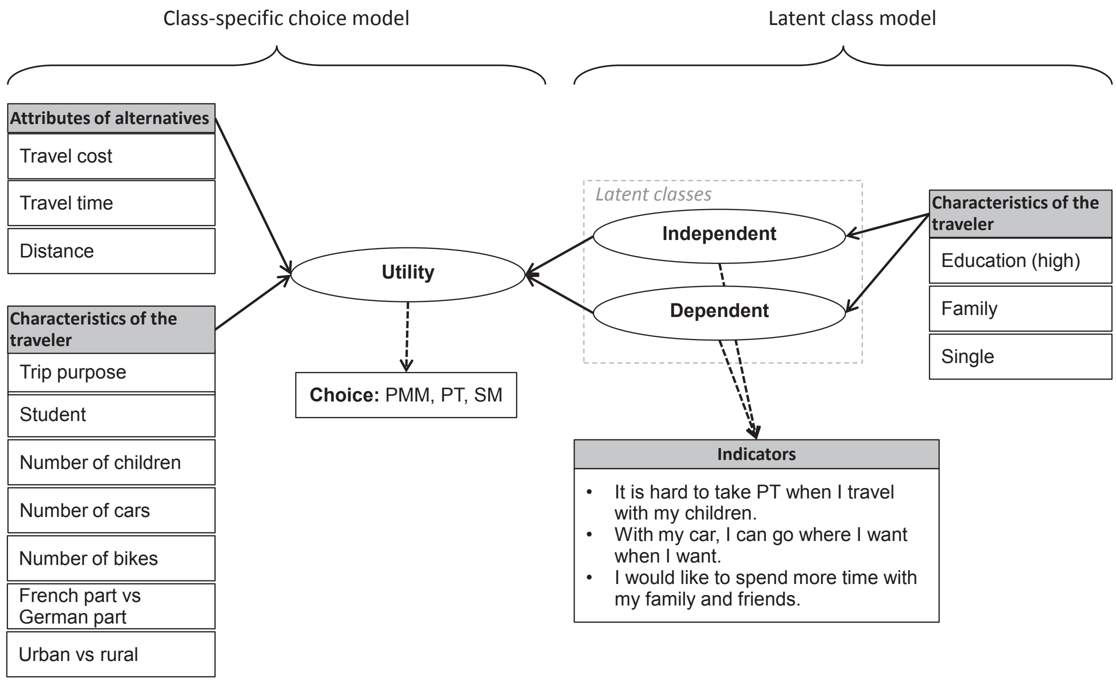


Figure 2: Discrete model framework

It is important to note that for the construction of structural equations for latent variables as well as the identification of latent classes, we have performed a factor analysis as an exploratory step with the relevant variables.

3.1 Continuous model

Psychometric indicators are studied using factor analysis techniques to identify the most important ones that explain the choice behavior. In Table 2 we present results for the first three factors with indicators having a factor loading higher than 0.2 (in absolute sense), which is used as the cut-off value. When we analyze the results, we observe that the first factor corresponds to a negative attitude towards public transport, being positively correlated with the indicators that are related to the inconvenience of public transport. When we do a similar analysis for factor 2 and 3, we observe that the second one is related to the environmental attitude and the third one represents the public transport awareness.

From these results we selected the first and second factors, and named them as *pro-car* and *environmental concern* respectively. For *pro-car* we included the indicators 8, 9 and 10 and for *environmental concern* we worked with 1, 2, 4 and 5 which were found to improve the model.

Table 2: Factor analysis results for indicators

Indicators	**Factor 1**	**Factor 2**	**Factor 3**
1- We should increase the price of gasoline to reduce congestion and air pollution.	-0.375	0.453	
2- We need more public transport, even if it means higher taxes.		0.410	
3- Environmentalism harms the small businesses.	0.237		
4- I am concerned about global warming.		0.674	
5- We must act and make decisions to reduce emissions of greenhouse gases.		0.675	
6- I'm not comfortable when I travel with people I do not know well.	0.342		
7- Taking the bus helps to make the city more comfortable and welcoming.		0.311	
8- Its hard to take public transport when I travel with my children.	0.448		
9- Its hard to take public transport when I travel with bags or luggage.	0.587		
10- I dont like to change transport modes when I travel.	0.493		
11- If I use public transport instead of my car, I have to cancel some activities.	0.563		
12- The bus schedule is sometimes hard to understand.	0.398		
13- I know well which bus or train I must take, regardless of where Im going.			0.709
14- I know the bus schedule by heart.			0.515
15- I use the Internet for schedules and departure times of buses or trains.			0.308
16- I have used public transport all my life.	-0.240		0.370
17- I know some of the drivers of the buses I take.			0.279

Structural equations for latent attitudes

In the latent variable model, the structural equations for the attitudes were built as specified in Table 3. The *pro-car* attitude is represented by A_{car} and the *environmental concern* is represented by A_{env}. The explanatory variables can be listed as follows:

- $\overline{A_{car}}$ and $\overline{A_{env}}$ are the constants for the corresponding attitudes,
- N_{cars} represents the number of cars in the household,
- a set of dummy variables ($Valais$, $Bern$, $Basel-Zurich$, $EastSwitzerland$, $Graubünden$) represent the regions that are in the German speaking part except $Valais$ where both French and German are spoken,
- $Educ$ is a dummy variable which is 1 for respondents who have a university degree,
- N_{bikes} is the number of bikes in the household,

- $Age \cdot (Age > 45)$ is a piecewise linear variable which is 0 for the individuals under age 45. Therefore individuals under the age of 45 constitute a reference value and the parameter is estimated for the remaining population.

Let us remark that the parameter for *Educ* variable is kept the same for the two attitudes, but introduced with a minus sign for *pro-car*. Indeed, considering separate parameters for both equations did not give significantly different results.

Table 3: Specification table of the structural equations of the continuous model

Attitudes	A_{car}	A_{env}
$\overline{A_{car}}$	1	-
$\overline{A_{env}}$	-	1
θ_{Ncars}	N_{cars}	-
θ_{educ}	$-Educ$	$Educ$
θ_{Nbikes}	-	N_{bikes}
θ_{age}	-	$Age \cdot (Age > 45)$
θ_{Valais}	$Valais$	-
θ_{Bern}	$Bern$	-
$\theta_{Basel-Zurich}$	$Basel - Zurich$	-
θ_{East}	$EastSwitzerland$	-
$\theta_{Graubünden}$	$Graubünden$	-

Measurement equations for latent attitudes

As mentioned previously, for the attitude *pro-car*, indicators 8, 9 and 10 were used and for *environmental concern*, indicators 1, 2, 4 and 5 were included in the model. Therefore, measurement equations were built with the corresponding indicators of the attitudes as given in equation (1).

$$I_k = \alpha_k + \lambda_k A + \upsilon_k \qquad \forall k, \tag{1}$$

where α_k and λ_k are parameters to be estimated. A denotes the latent attitudes. I_k represents the psychometric indicators. The error term υ_k is normally distributed with mean 0 and standard deviation σ_{υ_k}.

Structural equations for utilities

Mode choice is assumed to be between the alternatives of *private motorized modes (PMM)*, which include car as a user and passenger, motorbike and taxi, *public transport (PT)*, which consists of bus, train and car postal, and *soft modes (SM)*, that represents walking and bike. Utilities of the alternatives are defined with explanatory variables of modal attributes, individual characteristics and latent attitudes represented by Table 4.

Table 4: Specification table of the utilities

	Continuous model			Discrete model					Base model		
				Class independent			Class dependent				
Utilities	V_{PMM}	V_{PT}	V_{SM}	V_{PMM}	V_{PT}	V_{SM}	V_{PMM}	V_{PT}	V_{PMM}	V_{PT}	V_{SM}
ASC_{PMM}	1	-	-	-	-	-	-	-	1	-	-
ASC^1_{PMM}	-	-	-	1	-	-	-	-	-	-	-
ASC^2_{PMM}	-	-	-	-	-	-	1	-	-	-	-
ASC_{SM}	-	-	1	-	-	-	-	-	-	-	-
ASC^1_{SM}	-	-	-	-	-	1	-	-	-	-	-
β_{cost}	C_{PMM}	C_{PT}	-	-	-	-	-	-	C_{PMM}	C_{PT}	-
β^1_{cost}	-	-	-	C_{PMM}	C_{PT}	-	-	-	-	-	-
β^2_{cost}	-	-	-	-	-	-	C_{PMM}	C_{PT}	-	-	-
$\beta_{TT_{PMM}}$	TT_{PMM}	-	-	-	-	-	-	-	TT_{PMM}	-	-
$\beta^1_{TT_{PMM}}$	-	-	-	TT_{PMM}	-	-	-	-	-	-	-
$\beta^2_{TT_{PMM}}$	-	-	-	-	-	-	TT_{PMM}	-	-	-	-
$\beta_{TT_{PT}}$	-	TT_{PT}	-	-	-	-	-	-	-	TT_{PT}	-
$\beta^1_{TT_{PT}}$	-	-	-	-	TT_{PT}	-	-	-	-	-	-
$\beta^2_{TT_{PT}}$	-	-	-	-	-	-	-	TT_{PT}	-	-	-
$\beta_{distance}$	-	-	D_{SM}	-	-	-	-	-	-	-	D_{SM}
$\beta^1_{distance}$	-	-	-	-	-	D_{SM}	-	-	-	-	-
$\beta_{N_{cars}}$	N_{cars}	-	-	N_{cars}	-	-	N_{cars}	-	N_{cars}	-	-
$\beta_{N_{children}}$	$N_{children}$	-	-	-	-	-	-	-	$N_{children}$	-	-
$\beta^1_{N_{children}}$	-	-	-	$N_{children}$	-	-	-	-	-	-	-
$\beta^2_{N_{children}}$	-	-	-	-	-	-	$N_{children}$	-	-	-	-
$\beta_{language}$	$French$	-	-	$French$	-	-	$French$	-	$French$	-	-
β_{work}	$WorkTrip$	-	-	-	-	-	-	-	$WorkTrip$	-	-
β^1_{work}	-	-	-	$WorkTrip$	-	-	-	-	-	-	-
β^2_{work}	-	-	-	-	-	-	$WorkTrip$	-	-	-	-
β_{urban}	-	$Urban$	-	-	$Urban$	-	-	$Urban$	-	$Urban$	-
$\beta_{student}$	-	$Student$	-	-	$Student$	-	-	$Student$	-	$Student$	-
$\beta_{N_{bikes}}$	-	-	N_{bikes}	-	-	-	-	-	-	-	N_{bikes}
$\beta^1_{N_{bikes}}$	-	-	-	-	-	N_{bikes}	-	-	-	-	-
$\beta_{A_{car}}$	-	A_{car}	-	-	-	-	-	-	-	-	-
$\beta_{A_{env}}$	-	A_{env}	-	-	-	-	-	-	-	-	-

The explanatory variables used in the utilities are listed as follows:

- TT_{PMM} and TT_{PT} represent the travel time,
- C_{PMM} and C_{PT} are the travel costs,
- N_{cars} is the number of cars in the household,
- $N_{children}$ is the number of children under age 15 in the household,
- $French$ is a dummy variable being 1 for the respondents in the French speaking part,
- $WorkTrip$ is a dummy variable being 1 for the work related chain of trips,
- $Urban$ is a dummy variable representing the urban regions,
- $Student$ is a dummy variable for the respondents who are either a student or a trainee,
- D_{SM} is the total distance traveled.

Measurement equations for utility

Utilities of the alternatives are measured with the observed choices of the respondents as given in equation (2), where C_n is the choice set of individual n.

$$y_{in} = \begin{cases} 1 & \text{if } U_{in} \geq U_{jn}, \forall j \in C_n, \\ 0 & \text{otherwise.} \end{cases} . \tag{2}$$

Having defined the structural and measurement models for the latent attitudes and utilities, the likelihood of a given observation is built. It is given by the joint probability of observing choice and indicators of the latent attitudes.

3.2 Discrete model

In this section a discrete attitude model is presented where a latent segmentation of the individuals is simultaneously performed with the choice model. With the latent segmentation our aim is to identify the classes of travelers who have different sensitivities to changes in the attributes of the mode alternatives. We decided to work with two latent classes with different demand elasticities.

To start with a reasonable model, a factor analysis is performed as an exploratory analysis with socio-economic characteristics, psychometric indicators and the choice variable. This analysis provides information on the two segments of the individuals with respect to their characteristics and travel behavior.

Table 5: Results of factor analysis

	Factor 1	**Factor 2**
Choice PT		**0.250**
Socio-economic information		
$N_{children}$	**0.517**	
Student/trainee	0.117	**0.770**
N_{cars}	**0.203**	
HighIncome	**0.252**	
Education		-0.123
Age ≥ 60	**-0.375**	
Family status		
Couple without children	**-0.606**	
Couple with children	**0.927**	**-0.368**
Living with parents	0.159	**0.956**
Single	**-0.371**	
Single parent	-0.170	
Roommate	-0.142	
Psychometric Indicators		
PT children		
Flexibility car		-0.130
Family oriented	0.135	

The indicators included in the presented factor analysis are:

- **PT children:** *It is hard to take public transport when I travel with my children.*
- **Flexibility car:** *With my car, I can go where I want when I want.*
- **Family oriented:** *I would like to spend more time with my family and friends.*

It is observed that family attributes of individuals play an important role in the segmentation, together with their income level and age category. The factor loadings with an absolute value higher than 0.1 can be seen in Table 5, where the ones with an absolute value higher than 0.2 are presented in bold. Looking at the results, the two classes are defined as follows:

- **Class 1 - Independent**: Middle-aged individuals that live with their family and children, are typically active in the professional life, and have high income.
- **Class 2 - Dependent**: Young individuals who are mostly students and old people. This class of individuals are typically singles or couples without children.

The idea behind the naming of the classes is that the second group of individuals are either very young and students/trainees, which makes them economically dependent, or they are old, which limits their physical activities. We note that the factor loading for the indicator *PT children* is not strong. However, this indicator is included in the model since it is observed that it has a significant role in the segmentation as explained in section 3.3.

Structural equations for latent classes

With the help of the exploratory analysis the structural equations for the class membership model are built as in Table 6, where:

- *Family* is equal to 1 if the individual is living with his/her children, i.e. couples with children and single parent,
- *High Income* is 1 if household income is high,
- *Single* is 1 if the person lives either alone or with parents.

Although there were other characteristics suggested by the factor analysis, these are the ones who are estimated with success in the integrated model.

Table 6: Specification table of the structural equations of the discrete model

Latent class	$V_{independent}$	$V_{dependent}$
ASC_{ind}	1	-
γ_{family}	$Family$	-
γ_{income}	$HighIncome$	-
γ_{single}	-	$Single$

Measurement equations for the indicators

The class membership model is strengthened with the inclusion of the measurement model of psychometric indicators that are mentioned in the beginning of this section.

The probability of an individual n in latent class s giving a particular response r to an indicator k, $P(I_{nk} = r|s)$ for $r = 1,...,5$, which is called item-response probability, is defined as a parameter to be estimated from the model and measured with the psychometric indicators.

Structural equations for the utilities

For the two latent classes, *independent* and *dependent*, a specific mode choice model is developed. For the class *independent* we have all three alternatives available. However, the individuals belonging to the class *dependent* do not have the soft mode alternative. The reason is that a low proportion ($< 5\%$) of individuals in the dataset chose soft mode as their main mode. Therefore the second class, which includes the old people as well, did not allow the inclusion of soft mode. It is hence assumed that individuals belonging to class *dependent* do not consider soft mode as an alternative.

The specification of the utilities is displayed in Table 4 and is similar to the specification of the continuous model. The superscripts 1 and 2 are used to specify the latent class that the parameters are defined for. Superscript 1 specifies the latent class *independent* and superscript 2 is for the class *dependent*. Time and cost parameters are specific to each class to capture taste heterogeneity. Explanatory variables of $N_{children}$ and $WorkTrip$ are also defined specific to each class since the characteristics of classes significantly differ in terms of family attributes and professional life.

The specification of the measurement equations of the utilities for the discrete model are the same as the continuous model.

3.3 Estimation results

The maximum likelihood method is used for model estimation where the likelihood function is defined over the joint probability of observing the choice and the indicators of the latent components. The estimation is done by using the software package BIOGEME which allows for the estimation of advanced behavioral modeling as explained in Bierlaire and Fetiarison (2009). Estimation results are presented in Table 7 for the continuous model, the discrete model and the base model. The log-likelihood values and goodness of fit results are reported in Table 8 for the three models. The log-likelihood values for the continuous and the discrete models are calculated for only the choice probabilities to be comparable with the base model. It can be noticed that the discrete model has the best fit compared to the continuous and base models.

When we look at the utility parameters regarding the modal attributes of time, cost and distance, it is seen that they have the expected signs such that they affect the utility negatively. For the base model and the continuous model, the values of the estimates are close to each other. On the other hand, since latent class model allows the segmentation of the population, we have different sensitivities for the two classes. Individuals in the class *dependent* are more sensitive to the changes in travel cost and time, as expected. The differences in the time and cost sensitivities are also observed by looking at the demand elasticities and willingness to pay values, which will be discussed in section 4. Since we do not have the soft mode alternative for the second class, the distance parameter only appears in the utility of the first class. It results in a lower absolute value, compared to the other models, since *active* individuals are less sensitive to changes in distances.

The parameters for the other explanatory variables also have the expected signs and some further observations are presented below:

- The number of children in the household positively affects the utility of private motorized modes, since it brings the need for more flexible forms of transport. When we compare the continuous model with the base model, we observe that the value of the parameter becomes higher with the inclusion of the attitudes regarding the children. When we look at the latent class model, the effect is stronger for the individuals in class *independent* who are typically living with their children. On the other hand, the parameter is not significant for the class *dependent*, which prevents to make any conclusion, since the children related issues are not applicable to this class. Although it is not statistically significant, it is decided to be included for the purpose of presenting the different behavior of the latent segments.

- Individuals performing work related trips have a lower utility for private motorized modes which is expected due to the nature of these trips, being more frequent and almost identical from one day to the next. The latent class model allows to capture the fact that individuals in the class *dependent* do not behave in the same way since they are not active in professional life, being either students or retired people.

- The *pro-car* attitude decreases the utility of public transport and the effect increases with the number of cars in the household. On the other hand, individuals with high education and living in the German speaking part of Switzerland have a lower level of same attitude, which increases the utility of public transport.

- The *environmental concern* increases the utility of public transport so that the individuals who are sensitive to environmental issues use public transport more. This effect is more evident for the individuals with high level of education and increases with age and the number of bikes in the household.

- The integration of attitudes into the choice models enables us to see the effect of variables on the utilities as well as on the attitudes. In the continuous model, we have a variable N_{cars} both in the structural equation of *pro-car* and the utility of private motorized modes. Both parameters support that the utility of public transport decreases with the number of cars in the household. Similarly, N_{bikes} appears both in the structural equation of *environmental concern* and the utility of soft mode.

- Analyzing the results of the discrete model, individuals who are living with their children and have high income have higher probability to belong to class *indepen-*

dent. On the other hand, single individuals have higher probability to belong to class *dependent*. This shows that our assumptions based on the factor analysis is supported by the model.

For the measurement equations of the discrete model regarding the psychometric indicators, we provide the estimated item-response probabilities in Figure 3. We group the probabilities of responding 1 and 2 under the name of *No* and 4 and 5 under the name of *Yes*, and represent the probability of responding 3 as *Neutral (-)*. It is seen that individuals in class *dependent* have very high probability to give a neutral response to the the first indicator which is related to the difficulty of using public transport when traveling with children. This is parallel to our assumptions for defining the two classes as explained in section 3.2. The second indicator is related to the flexibility of car and for the two classes, we do not have very different response probabilities, but the probability to agree with the statement is higher for class *independent*. The last indicator is related to the desire to spend time with family and friends and the probability to give a higher value of response is higher for class *independent*, who are living with their family and having their social network. Including these class-specific item-response probabilities in the model strengthens the class membership model by considering the attitudes of individuals related to their travel behavior.

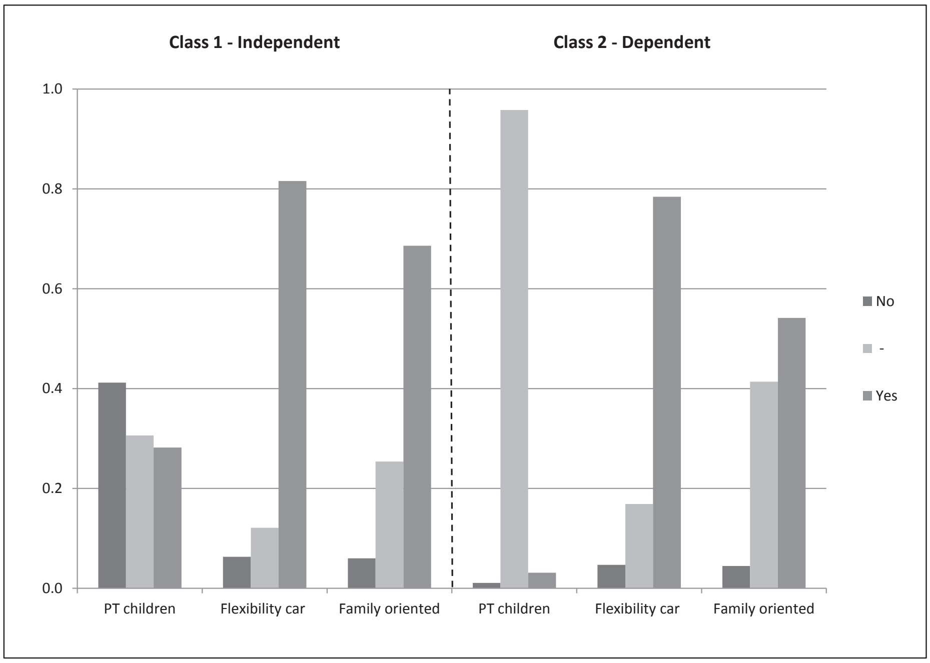


Figure 3: Estimated item-response probabilities

4 Model Application

The estimation results of the models presented in section 3 enabled us to uncover the variables explaining individuals' mode choices as well as characterizing population segments with different mobility behaviors. We will now explain how these results can be used to quantify the demand by defining several indicators. Moreover an analysis of the validity of the models will be provided.

4.1 Demand indicators

In this section, we present several aggregate indicators which reveal the demand of individuals for the different transport modes considered in this study. These indicators consist of *market shares*, *elasticities* and *values of time*.

Let us note that for the discrete model, the demand indicators were computed using the individual class membership probabilities. When these probabilities are weighted according to the representation in the population, their aggregate values are 54.5% for the *independent* class and 45.5% for the *dependent* class.

The first demand indicators that we are interested in are the market shares of each transport mode. Table 9 reports the market shares predicted by the logit model, the continuous model and the discrete model, for each mode. The latter do not vary much across models and are the highest for private motorized modes, ranging from 62.31% to 63.11%, the second highest for public transport, ranging from 31.20% to 32.35%, and the lowest for soft mode, ranging from 4.94% to 5.69%.

The market shares predicted by the continuous model differ from class 1, consisting of *independent* individuals, to class 2, representing *dependent* ones, since it cannot predict the choice for soft mode of individuals in class 2.

In order to evaluate the variations in the market shares caused by the increase or decrease of time and cost parameters, the second indicator we report in this paper are demand elasticities. The aggregate elasticities for the base model and the continuous model are computed using formula (3), to assess the effect on demand of changes in a variable $x \in \{C_{PMM}, TT_{PMM}, C_{PT}, TT_{PT}\}$ representing travel costs and times in private motorized modes and public transport, respectively.

$$E_x^i = \frac{\sum_{n=1}^{N} w_n P_n(i) E_{x_n}^i}{\sum_{n=1}^{N} w_n P_n(i)}, \tag{3}$$

where w_n is the sample weight described in section 2 for individual n, $P_n(i)$ is the probability that individual n chooses alternative i and $E_{x_n}^i$ is the elasticity of the demand of person n for variations in individual quantity x_n. The complete formula of this disaggregate elasticity is the following:

$$E^i_{x_n} = \frac{\partial P_n(i)}{\partial x_n}\frac{x_n}{P_n(i)}.$$

For the discrete model, the formula differs slightly since we need to include the membership probabilities to the classes of *independent* and *dependent* individuals. It is given as follows:

$$E^i_x = \frac{\sum_{n=1}^N w_n(P_n(i|Class1)\cdot P_n(Class1)\cdot E^{i,Class1}_{x_n} + P_n(i|Class2)\cdot P_n(Class2)\cdot E^{i,Class2}_{x_n})}{\sum_{n=1}^N w_n(P_n(i|Class1)\cdot P_n(Class1) + P_n(i|Class2)\cdot P_n(Class2))},$$

where $P_n(Class1)$ and $P_n(Class2)$ are the class membership probabilities for classes *independent* and *dependent*, respectively, for an individual n, $P_n(i|Class1)$ and $P_n(i|Class2)$ are the probabilities that n chooses alternative i given that he belongs to class *independent*, respectively class *dependent*, and $E^{i,Class1}_{x_n}$ and $E^{i,Class2}_{x_n}$ are disaggregate elasticities of the demand of person n for variations in individual quantity x_n, given that n belongs to class *independent*, respectively class *dependent*. Precisely, $E^{i,Class1}_{x_n}$ and $E^{i,Class2}_{x_n}$ are given by the following formulas:

$$E^{i,Class1}_{x_n} = \frac{\partial P_n(i|Class1)}{\partial x_n}\frac{x_n}{P_n(i|Class1)}$$

$$E^{i,Class2}_{x_n} = \frac{\partial P_n(i|Class2)}{\partial x_n}\frac{x_n}{P_n(i|Class2)}$$

Table 10 reports the aggregate demand elasticities for each of the three models. Let us first note that the latter are lower than 1 in absolute value, implying that demand is not very elastic with respect to changes in time and cost (Arnold, 2008). No obvious differences in the elasticities can be noticed between the base model and the continuous model. The elasticities for the discrete model are slightly higher.

The cost elasticities for private motorized modes are the lowest ($|\cdot| \leq 0.086$), implying that an increase of 1% in the travel costs for such modes, e.g. caused by an increase of the gasoline price, would result in a decrease in their market shares of less than 0.086%. For public transport, the cost elasticities are higher ($0.2 < |\cdot| < 0.3$), showing that an increase of 1% of travel fares results in a decrease of the market share of public transport slightly higher than 0.2%.

Time elasticities are higher than cost elasticities for all three models and this demonstrates that individuals are more sensitive to changes in travel durations than to changes in travel costs. Similar to cost elasticities, time elasticities computed for private motorized modes and public transport differ: the time elasticities for private motorized modes

$(0.234 < |\cdot| < 0.282)$ are lower than the ones for public transport $(0.465 < |\cdot| < 0.580)$, meaning that private motorized mode users are less sensitive to changes in their travel durations than users of public transport.

For the discrete model, differences occur in the sensitivity to variations in the travel costs and times. For individuals in the *dependent* class, i.e. class 2, an increase in the travel costs of 1% would result in a larger decrease in their probability to choose their current transport mode than for individuals in the *independent* class, i.e. class 1. This is consistent with the fact that individuals in class *independent* have larger incomes than individuals in class *dependent* (see Table 6 for the characterization of the classes). The same effect can be noticed for changes in travel times, i.e. individuals in class *dependent* are more sensitive to variations in travel durations than individuals in class *independent*.

The third demand indicator we investigate is the value of time. It expresses the willingness to pay of individuals to gain a travel duration of one hour. Table 11 reports the values of time for private motorized modes and public transport, predicted by all three models. It can be noticed that for both types of modes, the values of time do not differ much across models: for private motorized modes, the value of time is close to 30 CHF per hour and for public transport, it is slightly above 12 CHF per hour. These values are comparable with those reported in a study on the value of time in Switzerland (Axhausen et al., 2008). Precisely, that paper reports a value of time for public transport of 14.10 CHF per hour, which is close to our results, and a value of time for car travels of 20.98 CHF per hour, which is slightly lower than the values of time we obtained for the three models. Nevertheless, a similar trend appears between the study on the value of time and our research, which demonstrates that individuals are ready to spend more in order to gain time in private motorized modes than in public transport.

Let us also note that the values of time are different in the two classes of the discrete model. For both private motorized modes and public transport, they are higher for *independent* individuals. This can be explained by the fact that most of the individuals in this class are active workers for whom gaining an hour in travel is very important, contrary to part of the individuals in the *dependent* class who are students or retired persons. Let us remark that Axhausen et al. (2008) report a value of time of 27.66 CHF/hour for business travels in car, which is close to the value of time obtained for individuals in class *independent*.

In order to assess if the continuous model and discrete model presented in section 3 could be applied on other potential data sets, we perform a validation. As only one data set is available, that is, the one on which we calibrated the models, it is split into two parts. First we select randomly 80% of its observations and estimate the model on the latter and second we apply the model on the remaining 20% of the observations.

Histograms of the choice probabilities predicting the choice of the individuals in the 20% of the observations are shown in Figure 4 for the base model, the continuous model and the discrete model.

We observe that choice probabilities are well predicted by all three models, but best by the discrete model. As a confirmation of this result, Table 12 shows the percentages of choice probabilities higher than 0.5 and 0.9 for each model. For all three models, the percentage of choice probabilities above 0.5 and 0.9 are quite large, i.e. between 72% and 75% and between 25% and 28%, respectively. We notice that for the discrete model, the percentages of choice probabilities above 0.5 (75.00%) and above 0.9 (27.93%) are higher than for the two other models, which shows that the characterization of the two latent classes of *independent* and *dependent* individuals within the choice model results in a better prediction power.

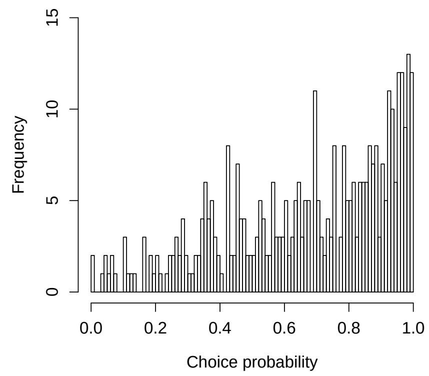
5 Conclusions and Future Research

In this paper we presented two models that aim at characterizing better mode choice behavior by using attitudinal indicators. In the first model, we integrated latent attitudes regarding public transport dislike and care for environment within a choice model. Moreover, in the second model, we could observe and capture heterogeneity in mode preferences for two different segments of the population via an integrated choice and latent class model.

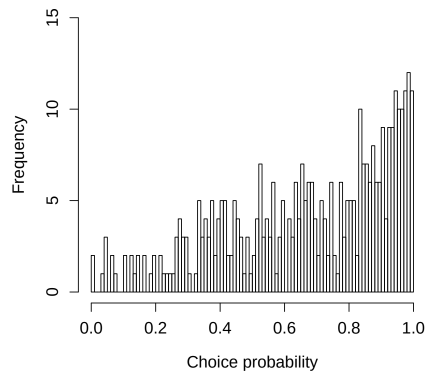
In order to analyze the demand for the different mode choices, several indicators are computed, i.e. market shares, elasticities and values of time. The indicators obtained for integrated choice and latent class model showed evidence of differences in the sensitivities to variations in the travel fares and durations between individuals of the two segments. Such model also demonstrated a higher prediction power over a simple logit model.

In the presented models the heterogeneity in the sample is explained through structural equation models for attitudinal variables. Therefore, provided that the necessary variables are available, the models can be applied for other samples. This is an added value of the presented models compared to mixtures of models which incorporate heterogeneity within the population through random distributions.

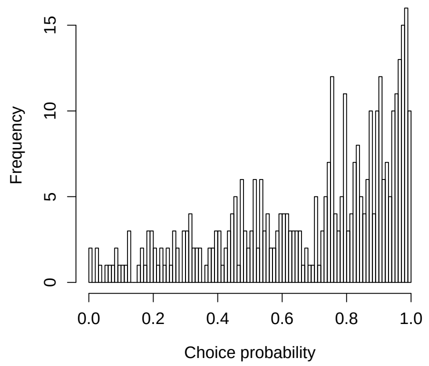
Regarding the specification of the integrated choice and latent variable model, further research could consist of the inclusion of more attitudinal variables as well as a better characterization of their indicators. The integrated choice and latent class model could



(a) Base model



(b) Continuous model



(c) Discrete model

Figure 4: Histograms of the choice probabilities

include additional classes. Finally, a combination of both models could be considered in order to have a comprehensive framework of the complexity and heterogeneity lying in the population.

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Table 7: Estimation results

	Continuous model		Discrete model		Base model	
Parameter	Estimate	t-test	Estimate	t-test	Estimate	t-test
Utilities						
ASC_{PMM}	-0.599	-0.810*	-	-	-0.413	-2.39
ASC^1_{PMM}	-	-	-0.945	-3.63	-	-
ASC^2_{PMM}	-	-	-0.936	-3.21	-	-
ASC_{SM}	-0.772	-0.930*	-	-	-0.470	-1.27*
ASC^1_{SM}	-	-	0.512	1.31*	-	-
β_{cost}	-0.0559	-5.11	-	-	-0.0592	-5.61
β^1_{cost}	-	-	-0.027	-2.74	-	-
β^2_{cost}	-	-	-0.302	-3.68	-	-
$\beta_{TT_{PMM}}$	-0.0294	-4.79	-	-	-0.0299	-4.96
$\beta^1_{TT_{PMM}}$	-	-	-0.0161	-2.59	-	-
$\beta^2_{TT_{PMM}}$	-	-	-0.111	-5.71	-	-
$\beta_{TT_{PT}}$	-0.0119	-4.40	-	-	-0.0121	-4.55
$\beta^1_{TT_{PT}}$	-	-	-0.00692	-2.5	-	-
$\beta^2_{TT_{PT}}$	-	-	-0.0445	-4.96	-	-
$\beta_{distance}$	-0.224	-4.25	-	-	-0.227	-4.28
$\beta^1_{distance}$	-	-	-0.199	-3.69	-	-
$\beta_{N_{cars}}$	0.970	9.88	1.23	9.8	1.00	10.3
$\beta_{N_{children}}$	0.215	3.23	-	-	0.154	2.37
$\beta^1_{N_{children}}$	-	-	0.404	4.64	-	-
$\beta^2_{N_{children}}$	-	-	-1.03	-1.19*	-	-
$\beta_{language}$	1.06	6.59	1.20	6.78	1.09	6.89
β_{work}	-0.583	-4.94	-	-	-0.582	-5.01
β^1_{work}	-	-	-0.785	-4.83	-	-
β^2_{work}	-	-	-0.130	-0.410*	-	-
β_{urban}	0.283	2.25	0.390	2.81	0.286	2.33
$\beta_{student}$	3.26	9.62	3.70	7.46	3.21	9.33
$\beta_{N_{bikes}}$	0.385	6.85	-	-	0.347	6.34
$\beta^1_{N_{bikes}}$	-	-	0.205	3.46	-	-
$\beta_{A_{car}}$	-0.574	-3.51	-	-	-	-
$\beta_{A_{env}}$	0.393	2.98	-	-	-	-
Attitudes						
$\overline{A_{car}}$	3.02	45.11	-	-	-	-
$\overline{A_{env}}$	3.23	66.49	-	-	-	-
θ_{Ncars}	0.104	4.37	-	-	-	-
θ_{educ}	0.235	6.92	-	-	-	-
θ_{Nbikes}	0.0845	7.42	-	-	-	-
θ_{age}	0.00445	2.22	-	-	-	-
θ_{Valais}	-0.223	-2.8	-	-	-	-
θ_{Bern}	-0.361	-4.74	-	-	-	-
$\theta_{Basel-Zurich}$	-0.256	-4.11	-	-	-	-
θ_{East}	-0.228	-3.21	-	-	-	-
$\theta_{Graubünden}$	-0.303	-3.37	-	-	-	-
Latent class						
ASC_{ind}	-	-	-0.629	-2.64	-	-
γ_{family}	-	-	3.92	3.8	-	-
γ_{income}	-	-	0.46	1.93	-	-
γ_{single}	-	-	0.704	3.51	-	-

(* Statistical significance < 90%)

Table 8: Statistics

	Continuous model	Discrete model	Base model
Log-likelihood	-1069.8	-1032.5	-1067.4
ρ^2	0.489	0.507	0.490

Table 9: Market shares

Model		PMM	PT	SM
Base model		62.31%	32.09%	5.60%
Continuous model		63.11%	31.20%	5.69%
Discrete model	Class 1	54.91%	36.13%	8.96%
	Class 2	65.73%	34.27%	-
	Overall	62.70%	32.35%	4.94%

Table 10: Demand elasticities

Model		PMM		PT	
		Cost elas.	Time elas.	Cost elas.	Time elas.
Base model		-0.064	-0.247	-0.216	-0.471
Continuous model		-0.058	-0.234	-0.202	-0.465
Discrete model	Class 1	-0.037	-0.165	-0.104	-0.275
	Class 2	-0.145	-0.425	-0.441	-0.879
	Overall	-0.086	-0.282	-0.263	-0.580

Table 11: Value of time

Model		PMM	PT
Base model		30.30 CHF/hour	12.26 CHF/hour
Continuous model		31.54 CHF/hour	12.81 CHF/hour
Discrete model	Class 1	35.78 CHF/hour	15.38 CHF/hour
	Class 2	22.05 CHF/hour	8.84 CHF/hour
	Overall	29.53 CHF/hour	12.40 CHF/hour

Table 12: Percentages of choice probabilities higher than 0.5 and 0.9

Threshold	Base model	Continuous model	Discrete model
0.5	72.87%	73.67%	75.00%
0.9	25.80%	25.53%	27.93%